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ABSTRACT

Correlation coefficients are frequently reported in educational and psychological research. The robustness properties and optimality among practical approximations when phi does not equal 0 with moderate sample sizes are not well documented. Three major approximations and their variations are examined: (1) a normal approximation of Fisher's Z, N(sub 1) (R. A. Fisher, 1915); (2) a student's t based approximation, t(sub 1) (H. C. Kraemer, 1973; M. Samiuddin, 1970), which replaces for each sample size the population phi with phi*, the median of the distribution of r (the product moment correlation); (3) a normal approximation, N(sub6) (H. C. Kraemer, 1980) that incorporates the kurtosis of the X distribution; and (4) five variations--t(sub2), t(sub 1)', N(sub 3), N(sub4), and N(sub4)'--on the aforementioned approximations. N(sub 1) was found to be most appropriate, although N(sub 6) always produced the shortest confidence intervals for a non-null hypothesis. All eight approximations resulted in positively biased rejection rates for large absolute values of phi; however, for some conditions with low values of phi with heteroscedasticity and non-zero kurtosis, they resulted in the negatively biased empirical rejection rates. Four tables contain information about the approximations. (Author/SLD)

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Robust approximations to the non-null distribution of the product moment correlation coefficient I: The Phi coefficient Abstract

Correlation coefficients are frequently reported in educational and psychological research. The robustness properties and optimality among practical approximations when $\rho \neq 0$ with moderate sample sizes are not well documented. Three major approximations and their variations are examined: a normal approximation of Fisher's Z, N₁ (Fisher, 1915); a Student's t based approximation, t₁ (Kraemer, 1973; Samiuddin, 1970), which replaces for each sample size the population ρ with ρ^* , the median of the distribution of r; a normal approximation, N₆ (Kraemer, 1980), which incorporates the kurtosis of the X distribution; and five variations (t₂, t₁', N₃, N₄, N₄') on the aforementioned approximations. N₁ was found to be most appropriate, though N₆ always produced the shortest confidence intervals for a non-null hypothesis. All eight approximations resulted in positively biased rejection rates for large absolute values of ρ but for some conditions with low values of ρ with heteroscedasticity and nonzero kurtosis resulted in the negatively biased empirical rejection rates.

Key words: Pearson Correlation, Phi coefficient, Robustness, Non-null distribution



Introduction

The distribution of the product moment correlation has been widely investigated. In particular, the mathematical and empirical properties of the null distribution ($\rho = 0$) and its robustness have been extensively investigated (Duncan & Layard, 1973; Edgell & Noon, 1987; Fisher, 1915; Gayen, 1951; Kowalski, 1972; Kraemer, 1980; Pearson, 1931, 1932; Ramussen, 1987; Zimmerman, 1986).

Let r be the product moment correlation coefficient between two random variables X and Y with ν degrees of freedom. Then, the test statistic for H₀: $\rho = 0$ is

$$T(r|0, \nu) = \nu^{1/2} r(1 - r^2)^{-1/2}$$
. [1]

When the parent distribution is bivariate normal, [1] distributes exactly as Student's t with $\nu = n - 2$ degrees of freedom, and as N(0,1) for large sample sizes.

The general consensus for $\rho=0$ is that the normal approximation is robust even with small sample sizes when the parent distribution is bivariate nonnormal (Gayen, 1951; Havlicek & Peterson, 1977; Norris & Hjelm, 1961; Pearson, 1931, 1932; Zimmerman, 1986) provided that $\rho=0$ implies independence between the two variables (Duncan & Layard, 1973; Edgell & Noon, 1987; Kowalski, 1972). The exception is given to the contaminated normal variables where $\rho=0$ does not imply independence between the two variables. As an alternative to applying the normal-r theory to the correlations obtained from bivariate nonnormal distributions, Duncan and Layard (1973) have proposed a bootstrapping method for testing $\rho=0$. Ramussen (1987), however, has shown that the normal approximation based on Fisher's Z transformation using in testing non-null correlations is superior to the bootstrapping in testing $\rho=0$ for a nonnormal distribution satisfying the independence condition.

Compared to the extensive research on the null distribution of r, the studies on the non-null distribution are comparatively few (Fowler, 1987; Gayen, 1951; Haldane, 1949; Kraemer, 1973, 1980; Samiuddin, 1970). Gayen (1951) has derived the mathematical expression for the approximate sampling distribution of r for nonnormal distributions by incorporating the information up to the 4th joint moments between X and Y. Although Gayen has shown that a



simpler approximation to his derivation is satisfactory, his approximation is of little practical value because it is still computationally cumbersome and it requires the specification of the population joint moments, which are rarely known to a researcher.

The most frequently adopted strategy for $\rho \neq 0$ is Fisher's Z transformation, which is defined as

$$Z_{\Gamma} = 1/2 \ln \left[(1+r)/(1-r) \right],$$
 [2]

and is approximated by N_1 when sample sizes are large. N_1 is a normal distribution with

$$\mu = 1/2 \ln [(1+\rho)/(1-\rho)] + \rho/\{2(n-1)\} \{1 + (5+\rho^2)/4(n-1)\}, \text{ and}$$
 [3]

$$\sigma^2 = \{1/(n-1)\}\{1 + (4 - \rho^2)/2(n-1) + (22 - 6\rho^2 - 3\rho^4)/[6(n-1)^2]\}.$$
 [4]

A simpler but less accurate approximation, N₃, is again a normal distribution with

$$\mu = 1/2 \ln [(1+\rho)/(1-\rho)], \text{ and}$$
 [5]

$$\sigma^2 = 1/(n-3)$$
. [6]

Gayen has reported that N_1 considerably influenced by nonnormality when $\rho \neq 0$ and the normal approximation shows a satisfactory fit only for very large sample sizes. As an alternative to Fisher's Z, Samuiddin (1970) and Kraemer (1973) have proposed another transformation, T.

$$T(r|\rho, \nu) = \nu^{1/2} (r - \rho) [(1 - r^2) (1 - \rho^2)]^{-1/2},$$
 [7]

and it is approximately distributed as t with $\nu = n - 2$ degrees of freedom. The approximation t_1 replaces ρ in [7] with ρ^* , the median of the distribution of r, (David, 1938; Kraemer, 197;),

$$T(r|\rho^*, \nu) = \nu^{1/2} (r - \rho^*) [(1 - r^2) (1 - \rho^{*2})]^{-1/2}.$$
 [8]

Kraemer (1973) has reported that t_1 is most accurate for $|\rho| \le .7$, while N_1 is most accurate when ρ is near unity ($|\rho| \ge .80$) by showing the maximum deviations of the approximate cumulative distribution from the actual cumulative distribution. When ρ^* is replaced with r, t_2 approximation is obtained. The t_2 approximation is reportedly satisfactory for n > 25 (Kraemer, 1973).

Yet another derivation, which is a large sample approximation of t1, is N4. N4 is approximately normal with the following mean and variance:



$$\mu = 1/2 \ln \left[(1+p^*)/(1-p^*) \right], \text{ and}$$
 [9]

$$\sigma^2 = \{1/(n-1)\} + [2/\{(n-1)(n+1)\}] + [23/[3(n-1)(n+1)(n+3)\}].$$
 [10]

Kraemer (1980) has examined yet another large sample approximation, N₆. N₆ is a large sample approximation of [7] which incorporates the kurtosis, $\lambda (\mu 4/\sigma_x^2 - 3)$ of the X-distribution. The T statistic distributes approximately normal as

$$T(r|\rho, \nu) \sim N(0, 1 + \rho^2 \lambda/4).$$
 [11]

An optimal approximation for $\rho \neq 0$ for bivariate nonnormal distributions has not been determined because a direct comparison among t_1 , N_1 , and N_6 , has not been conducted. The optimality conditions reported in Kraemer (1973) are focused on the maximum discrepancy for the entire area of the sampling distribution and not on the tails or on the confidence intervals for frequently chosen coverages. Consequently, the approximation with the largest maximum error in her study may not necessarily be the worst approximation in terms of the test sizes and the typically used confidence intervals.

Because N_1 , t_1 , N_4 , t_2 , N_3 , and N_6 require the knowledge of the population parameter ρ , they can be used in testing an assigned value of ρ . However, the size of ρ is rarely known to the researcher, therefore, these are not practical in setting the confidence intervals for the unknown ρ unless the variance is independent of the parameter. For N_4 , and N_3 , a confidence interval can be derived for an unknown ρ because their variance estimates depend on the sample size alone.

For t_1 and N_4 , it is also possible to derive a correction factor for ρ which does not depends on the size of ρ . The median of the ρ^* , ρ' , which is the median of the medians obtained from the sampling distributions of r for a set of given ρ and n, was derived for the current study. The values of ρ^* are dependent on both ρ and n, but the values of ρ' are independent of the population ρ and they can be determined for each sample size. A table of the correction factors, $\rho' - \rho$ are presented in Table 1. The researcher, based on the sample size, for example, n = 12, can tell that the confidence limits for ρ should be adjusted by 0.0138 from the confidence



limits set for ρ' . The procedures using ρ' are t_1' and N_4' , each corresponds to t_1 and N_4 , respectively. As stated before, the procedure t_2 uses ρ in place of ρ^* in the equation for t_1 .

Table 1. Correction factor for non-zero o given the sample size

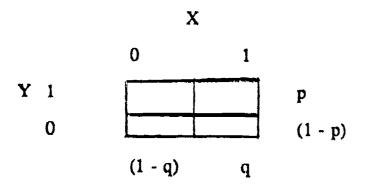
n	correction factor
12	0.0138
22	0.0069
32	0.0501
42	0.0039
52	0.0028
102	0.0015
202	0.0007

Gayen (1951) reported that Fisher's Z transformed variable was considerably influenced by the non-normality if $\rho \neq 0$. The relative efficiency and robustness of these eight approximations is not well known. The results reported in Kraemer (1973) are based on normal distributions where t_1 was found to be the optimal approximation as long as ρ was not too large; for $\rho > .80$, Fisher's N_1 approximation showed a better fit to the empirical distribution of r than t_1 . Again, these results did not compare all eight procedures, nor were they concerned with typically selected test sizes or confidence interval coverages. Furthermore, the results are not well cumulated for the product moment correlation for discrete variables, namely, the Phi coefficient.

The Phi coefficient

Given X and Y are discrete variables taking on 0 and 1, let p be the probability of 1 in X variable and q be the probability of 1 in Y. The range of the product moment coefficient, which is called the Phi-coefficient will be limited by the values of p and q.





Kraemer (1980) examined the robustness properties of the asymptotic normal distribution theory based on three assumptions: linearity, homoscedasticity, and zero kurtosis. The Phi coefficients were presented as an example nonnormal distribution with linearity trivially satisfied and for p = q = 0.5, the homoscedasticity condition is also met. The kurtosis of the X distribution is reflected in the variance of N₆ as $(1 + \rho^2 \lambda/4)$, where $\lambda = \mu_4/\sigma^4 - 3$ in general, and is equal to [1 - 6p(1 - p)]/4p(1 - p) when X is discrete. She showed that for $\rho \neq 0$, even with both linearity and homoscedasticity being satisfied, the normal approximation, N₆, showed sizable deviations from the empirical distribution of r and that this trend became pronounced as ρ increased. Furthermore, her Monte Carlo study indicated that N₆, which incorporates the kurtosis of the X-distribution, was extremely discrepant from the sampling distribution of the ϕ -coefficient when $\rho \neq q$, where heteroscedasticity also existed. The performance of the other seven approximations nor the performance of N₆ with respect to test sizes and confidence intervals are not yet known.

Purpose of the Study

The purpose of this study is to examine robustness of the three approximations, t_1 , N_1 , N_6 , and their five variations, t_1 ', t_2 , N_3 , N_4 , and N_4 ', to the non-null distribution of the product moment correlation coefficient, the Phi coefficient, when the parent distribution is bivariate nonnormal. This research extends the work on the effect of heteroscedasticity and kurtosis by Kraemer (1980) for the Phi coefficient. It may be argued that a Chi-square distribution is often applied to a function of the Phi-coefficient in testing $\phi = 0$ and not a normal approximation to the Phi-coefficient itself, therefore, a direct normal approximation may not be needed in testing



non-null hypotheses either. However, as we recall that a Chi-square is the squared normal distribution, they are both rooted from the same asymptotic assumptions.

An investigation in this area is most useful in applied research, because (1) a researcher rarely encounters a perfectly bivariate normal distribution; (2) a researcher cannot always secure a large enough sample size to depend on the large sample normal-r theory; and (3) a researcher in a substantive area is likely to be dealing with $\rho \neq 0$ rather than $\rho = 0$ and accurate confidence intervals are indispensable in cumulating research efforts in the field.

Method

A computer simulation method is used to investigate robustness of eight approximations when $\rho\neq 0$. Random numbers are generated using the International Mathematical Subroutine Libraries (IMSL, 1989). A computer program for this study was benchmarked against the tabled data reported by Kraemer (1980, pp.173-174) for the ϕ -coefficient. All experimental conditions had 1000 replications for each of the following conditions: two nominal α levels: 0.05, 0.01; four sizes of ρ : .2, .4, .6, and .8; and six sample sizes: 12, 22, 32, 52, 102, and 202. The distributions with p=q=0.5, $p=q\neq 0.5$ (p=q=0.25 and p=q=0.75), and $p\neq q$ (p=0.25 q=0.75 and p=0.50 q=0.75) were generated using the definitions for 2×2 cell probabilities presented by Hamden (1949) and Kraemer (1980). The values of p and q limit the range of possible p, therefore, certain combinations were not examined because it was impossible to generate.

Results

Along with the confidence limits, the length of the confidence interval, empirical test size for testing $\rho = \rho_0$ ($\rho_0 \neq 0$) at $\alpha = 0.05$, the sample r_{max} and r_{min} value (Caroll, 1954; Guilford, 1949) which indicate the range of the sampling distribution of r, are reported in the tables. Because the 1% results were very similar to the 5% counterparts in their trend, the selected results for the 5% are summarized in Tables 2 to 4.

As the sample sizes reached over 30, all eight approximations were practically the same. For low r values with p = q = 0.5, all approximations were equally good except for N₆, which



consistently showed a positive test size bias. In general, N_6 showed the shortest confidence intervals followed by N_1 ; and N_6 showed the largest test size of all eight approximations. For $\Phi \neq 0$ with p = q = 0.5, basically all eight approximations except N_6 behaved similarly for the conditions tested (Table 2). N_6 showed a decisive positive bias in its test size which did not diminish until n > 40 in testing $\Phi = .20$. Once $\Phi \geq .40$, all eight approximations started to increase their test sizes. As reported in Kraemer (1980), N_6 did not well behave when Φ became large. From this study, it is also clear that any other approximations aid not behave well for $\Phi \geq .80$ (Table 3). When $p \neq q$, t_1 and t_1 both increased their test sizes but they were still favorable to t_1 0. t_2 1 seems to show the inflated Type I errors and the tendency becomes worse for certain conditions of t_1 2 and t_2 3 and t_3 4. However, for some other heterogeneity condition such as t_1 3 and t_2 4 and t_3 5 with t_3 6. However, for some other heterogeneity condition such as t_3 6 and t_3 7 and t_3 8. However, for some other heterogeneity condition such as t_3 7 and t_3 8 eight approximations showed negatively biased test sizes (Table 4).

Discussion

Although uncritical extrapolation of the preliminary simulation results should be avoided, all eight approximations were very close even for small sample sizes. N_6 consistently showed the shortest confidence intervals for all conditions, however, it also showed a larger positive bias in its test size in comparison to the immediate competitor, N_1 . The unexpected result was that N_6 consistently showed its poor performance. Even the simplest approximation, N_3 , seemed to be more robust and accurate than N_6 . Another surprize was that even with p=q=0.5, thus, the homoscedastic condition is thet, all eight approximations were not satisfactory for the large absolute value of ϕ . A practical guidance may be to adopt N_3 in general but there is no optimal approximation so far for large absolute values of ϕ . Currently we are investigating several alternative approximations for the conditions with relatively high values of ϕ .



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Table 2. Eight approximations for the non-null correlation coefficient with $\rho=0.2$ and p=q=0.5

sample size	N1	t1	N6	t2	t1'	N3	N4	N4'
(r _{min} , r, r _{max})								
N = 12								
(719, .208, .751)								
95% Confidence limits	(357, .667) (37	77, .664) (3	353, .665) (-	.367, .674)	(381, .660)	(365, .672)	(368, .659)	(372, .655
[Length of CI]	[1.024]	[1.041]	[1.018]	[1.041	[1.041]	[1.037]	[1.027]	[1.027]
Rejection rates at 5% ^a	0.061	0.057	.084	.057	.057	.057	.061	.061
N = 22								
(789, .198, .808)								
95% Confidence limits	(222, .558) (23	30, .556) (2	217, .555) (-	.225, .561)	(231, .554)	(223, .560)	(227, .554)	(229, .552)
[Length of CI]	[.780]	[.786]	[.773]	[.785]	[.785]	[.783]	[.781]	[.781]
Rejection rates at 5% ^a	.046	.046	.070	.046	.046	.049	.046	.046
N = 32								
(808, .202, .845)								
95% Confidence limits	(144, .506) (15	50, .504) (:	141, .504) (.146, .507)	(151, .502)	(145, .507)	(148, .503)	(150, .501)
[Length of CI]	[.650]	[.654]	[.645]	[.653]	[.653]	[.652]	[.651]	[.651]
Rejection rates at 5% ^a	0.068	.068	.078	.068	.0650	.068	.068	.065

a 95% SE of simulation = .0135, providing (.0365, .0635) as a CI for the nominal level of 5%.

Table 3. Eight approximations for the non-null correlation coefficient with $\rho=0.8$ and p=q=0.5

sample size	N1	t1	N6	t2	t1'	N3	N4	N4'
(r _{min} , 1, r _{max})								
N = 12						··		<u></u>
(676, .875, .800)								
95% Confidence limits	(.501, .935) (.473,	.924) (.531,	, .929) (.487,	.938) (.473,	.924) (.489	, .937) (.480	0, .923) (.480), .923)
[Length of CI]	[.434]	[.451]	[.397]	[.451]	[.451]	[.448]	[.443]	[.443]
Rejection rates at 5% ^a	0.320	.320	.342	.318	.320	.318	.320	.320
N = 22								
(752, .795, .900)								
95% Confidence limits	(.584, .908) (.574	, .903) (.606	5, .901) (.580	, .909) (.573	, .902) (.58	1, .909) (.57	5, .902) (.57	5, .902)
[Length of CI]	[.324]	[.329]	[.295]	[.329]	[.329]	[.328]	[.327]	[.327]
Rejection rates at 5% ^a	0.154	.154	.389	.145	.154	.145	.154	.154
N = 32								
(775, .800, .915)								
95% Confidence limits	(.637, .896) (.631	, .893) (.654	, .890) (.636	, .897) (.630	, .892) (.636	5, .897) (.63	1, .892) (.63	1, .892)
[Length of CI]	[.259]	[.262]	[.236]	[.261]	[.261]	[.261]	[.261]	[.261]
Rejection rates at 5% ^a	0.253	.253	.266	.228	.253	.232	.253	.253

a 95% SE of simulation = .0135, providing (.0365, .0635) as .. CI for the nominal level of 5%.



Table 4. Eight approximations for the non-null correlation coefficient with $\rho=0.2$ and p=0.25 q = 0.75

sample size	N1	t1	N6	t2	t1'	N3	N4	N4'	
(r _{min} , r, r _{max})									
N = 12									
(698, .194, .334)									
95% Confidence limits	(392, .668) (412, .665)	(390, .667)	(403, .675)	(416, .661)	(400, .673)	(403, .660)	(408, .656	
[Length of CI]	[1.060]	[1.078]	[1.058]	[1.078]	[1.078]	[1.073]	[1.063]	[1.063]	
Rejection rates at 5%a	0.026	.020	.034	.020	.020	.020	.026	.026	
N = 22									
(741, .205, .331)									
95% Confidence limits	(228, .564) (237, .562)	(226, .562)	(231, .567)	(238, .560)	(230, .566)	(234, .560)	(236, .558	
[Length of CI]	[.793]	[.799]	[.788]	[.798]	[.798]	[.796]	[.794]	[.794]	
Rejection rates at 5% ^a	0.023	.023	.027	.015	.023	.015	.023	.023	
N = 32									
(777, .196, .330)									
95% Confidence limits	(156, .504) (154, .503)	(157, .505)	(162, .500)	(156, .505)	(160, .501)	(161, .500)	(162, .500	
[Length of CI]	[.660]	[.663]	[.656]	[.663]	[.663]	[.661]	[.661]	[.661]	
Rejection rates at 5% ^a	0.018	.017	.021	.017	.018	.017	.018	.018	

a 95% SE of simulation = .0135, providing (.0365, .0635) as a CI for the nominal level of 5%.